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Critical Scenario Creation for Verification and Validation of Cooperative and Automated Driving functionalities

Where today meets tomorrow.

The AV Development Challenge

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How to reach full automation as soon as possible?

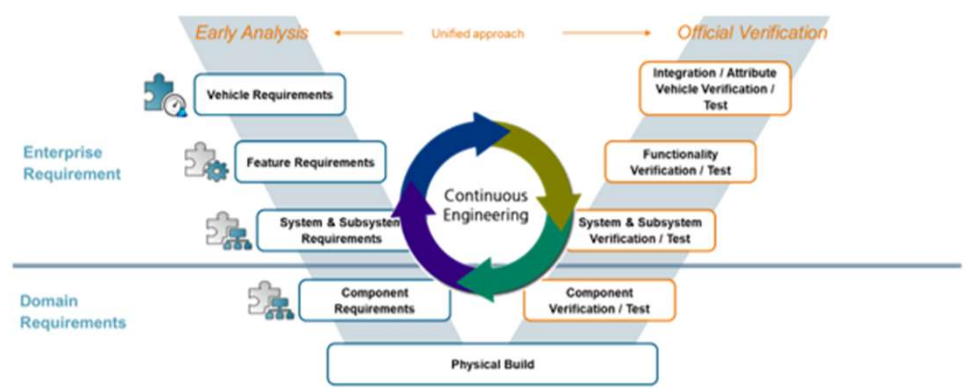
- **Automated vehicles are highly complex systems, as they have to operate safely and reliably in diverse driving environments.**
- **Testing of autonomous vehicles is a challenging problem which cannot be efficiently handled with conventional approaches.**
- **Lack of efficient testing can affect time-to-market. "14.2 billion miles of testing is needed" Akio Toyoda, CEO of Toyota Paris Auto Show 2016**

There are many scientific in-depth discussions on the challenges of safety validation for autonomous vehicles, arguing that digitalization and virtual testing should be the main target for both methodological and economic reasons.

Introduction

To assess the safety of automated vehicles various aspects must be taken into account:

- Safe functionality must be ensured through functional safety, as described in ISO 26262. This standard focuses on hazards induced by technical failures due to systematic and random faults in both hardware and software.
- Additionally, the so-called Safety of the Intended Functionality (SOTIF) must be ensured. **SOTIF** focuses on an intended function that could induce hazards due to functional insufficiencies, in the absence of technical system failures. SOTIF analysis covers identification of system weaknesses as well as **scenarios that lead to a hazardous event.**



Introduction (SOTIF)
safety of the intended functionality

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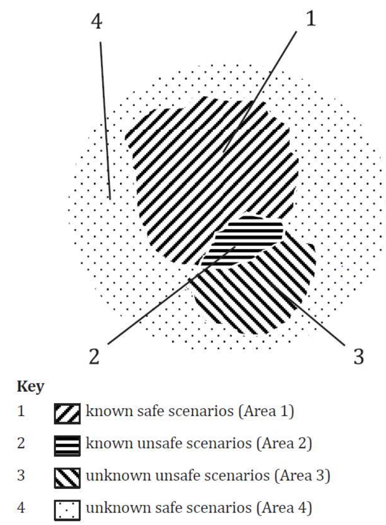
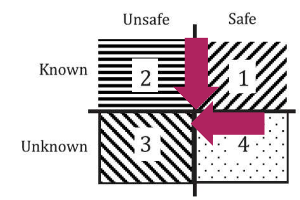
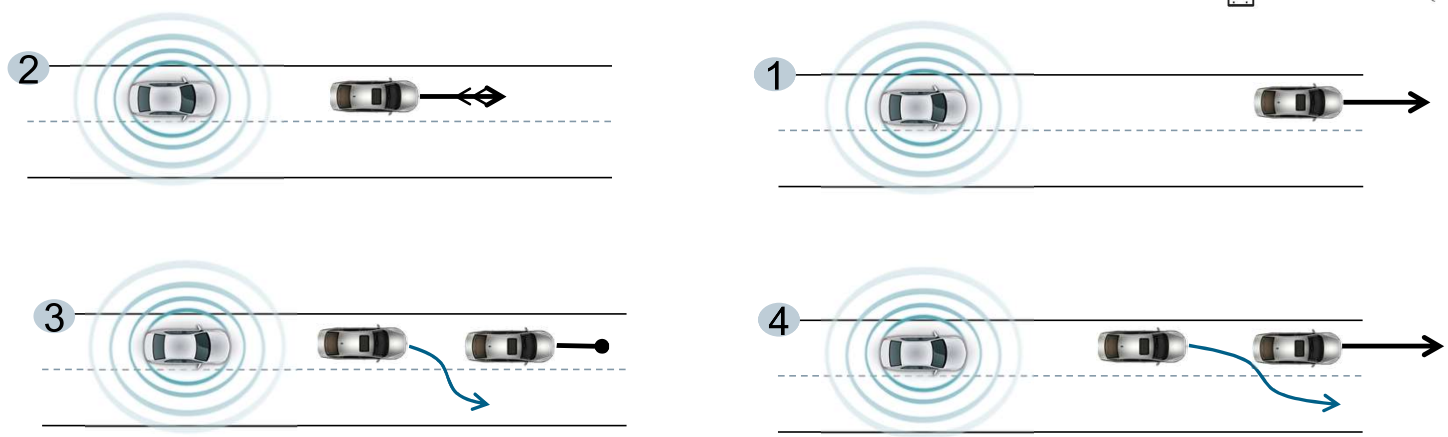




Objectives of SOTIF:

- Decrease area 3 by identifying unknow-unsafe scenarios



Siemens Solution for Creation of Unknown-Unsafe Scenarios

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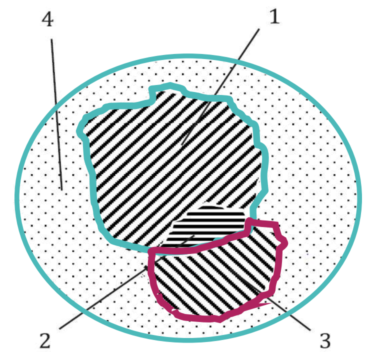

Key

1 known safe scenarios (Area 1)

2 known unsafe scenarios (Area 2)

3 unknown unsafe scenarios (Area 3)

4 unknown safe scenarios (Area 4)

Phase I:
Data collection,
Post-Processing &
3D Env. generation

→

Phase II:
Scene selection &
Basic scenario
elements extraction

→

Phase III:
Massive scenario &
test case generation

→

Phase IV:
Generation of
Unknown-Unsafe
Scenarios

Phase I: Data collection, Post-Processing & 3D Env. generation

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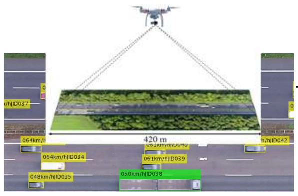
Real Data



Data

Post processing Drone

Data

Post processing infrustructure

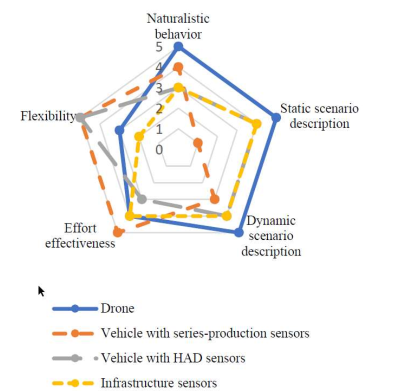
Data

Post processing Carlab

Data

Post processing fleet

Synthetic Data



[Automated Driving Department, Institute for Automotive Engineering RWTH Aachen University (Aachen, Germany)]

Phase I: Data collection, Post-Processing & 3D Env. generation
How?

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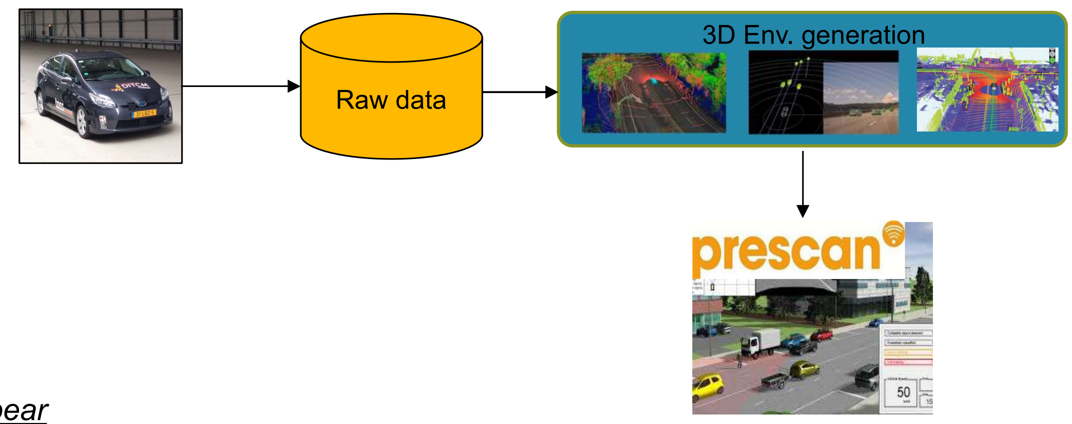
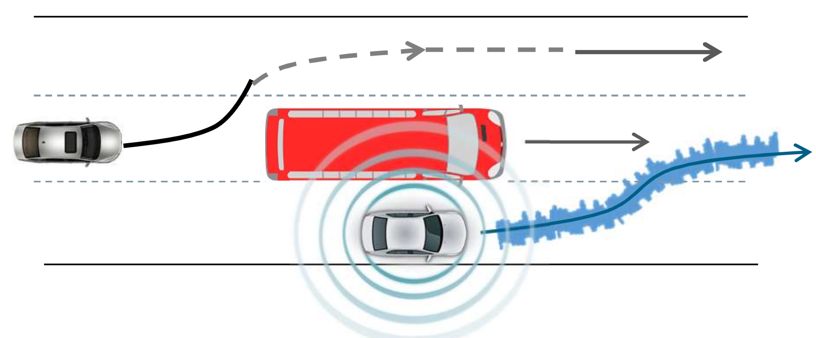
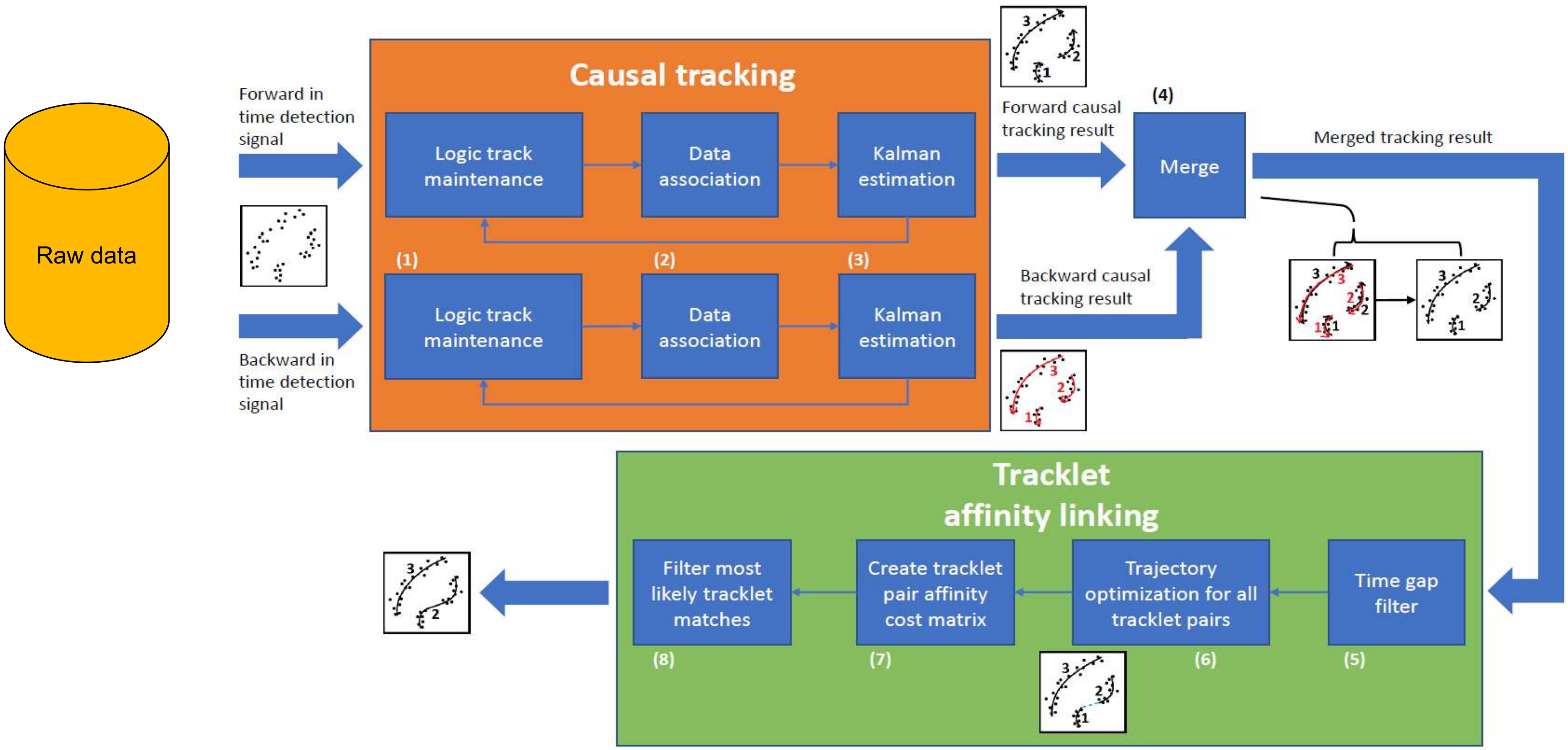
3D Environment generation:

- Generation of HD Map from static objects:
  - Sensor fusion
  - Object labeling and road sign detection
- Tracking of dynamic objects:
  - Host vehicle tracking
    - <u>*Smooth trajectory*</u>
  - Target vehicles tracking
    - <u>*Consistent/Stable tracking even if objects disappear from sight of the sensors for few seconds*</u>
  - Other road users tracking
- Map matching and localization of the road users trajectories with the generated map





Stable tracking



Stable tracking: causal tracking

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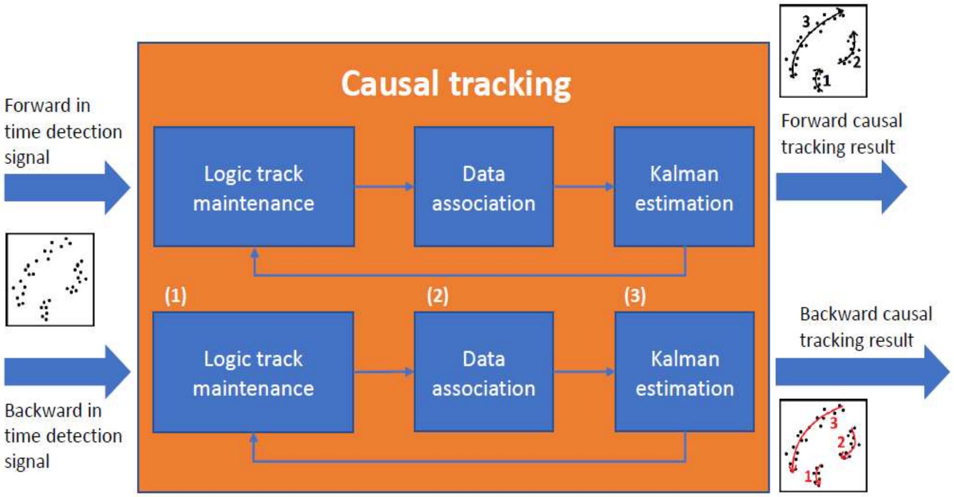
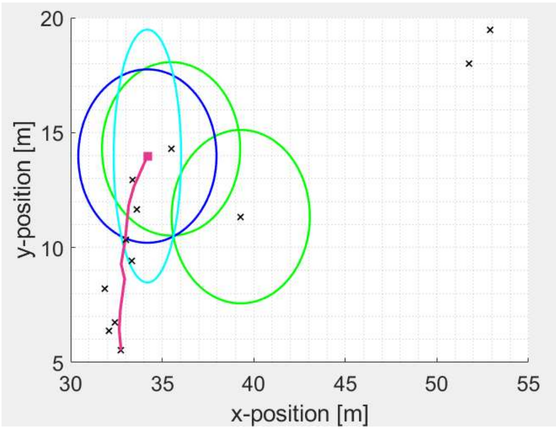
Logic track maintenance

- “New-track gate” placed around measurement,
- “Data association gate” around each object, measurements outside gate will be not be assigned.
- A tentative object





Stable tracking: causal tracking

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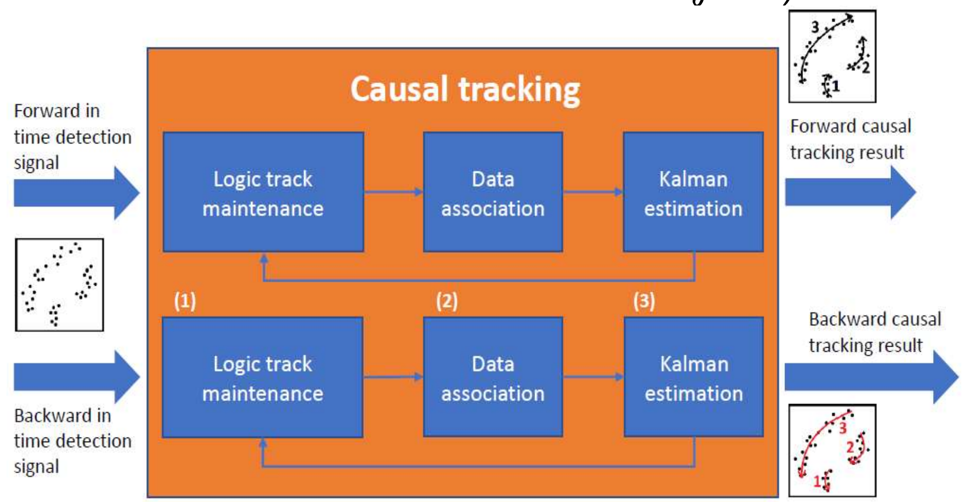
Data association

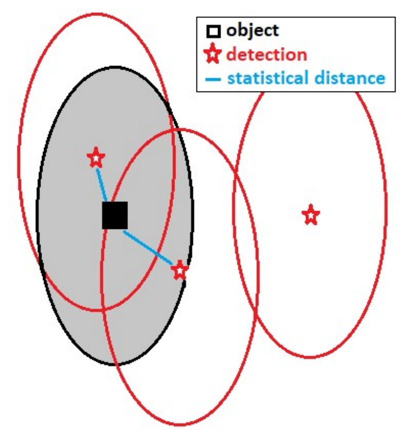
- Gated joint probability data association (JPDA)



Statistical distance: $d_{M,j,i} = \sqrt{(\hat{x}_j - \bar{x}_{m,i})^{\mathsf{T}} \Phi_m^{-1} (\hat{x}_j - \bar{x}_{m,i})}$

Weighting: $\alpha_{j,i} = \frac{\left(\frac{1}{d_{M_{j,i}}}\right)}{\sum_{i=1}^{n} d_{M_{j,i}}}$

Result: $x_{meas,JPDA,j} = \sum_{i=1}^{n} (\alpha_i x_{meas,i})$



Stable tracking: causal tracking

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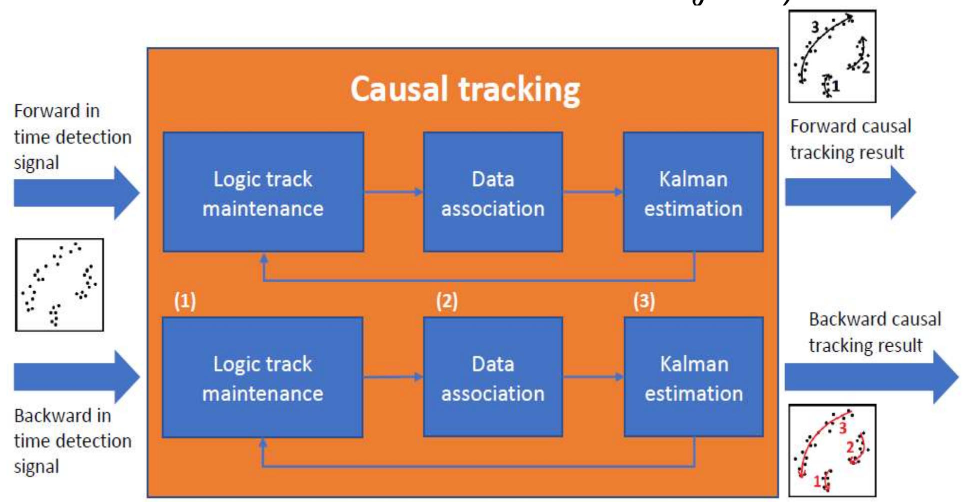
Kalman estimation

constant acceleration model
in discrete time, with sample time τ:



$$x_{k+1} = \underbrace{\begin{bmatrix} 1 & 0 & \tau & 0 & \frac{\tau^2}{2} & 0 \\ 0 & 1 & 0 & \tau & 0 & \frac{\tau^2}{2} \\ 0 & 0 & 1 & 0 & \tau & 0 \\ 0 & 0 & 0 & 1 & 0 & \tau \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{A_d} x_k \qquad y_k = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}}_{B_d} x_k \qquad x_k = \begin{bmatrix} p_{x,k} \\ p_{y,k} \\ v_{x,k} \\ v_{y,k} \\ a_{x,k} \\ a_{y,k} \end{bmatrix}$$

Stable tracking: merge

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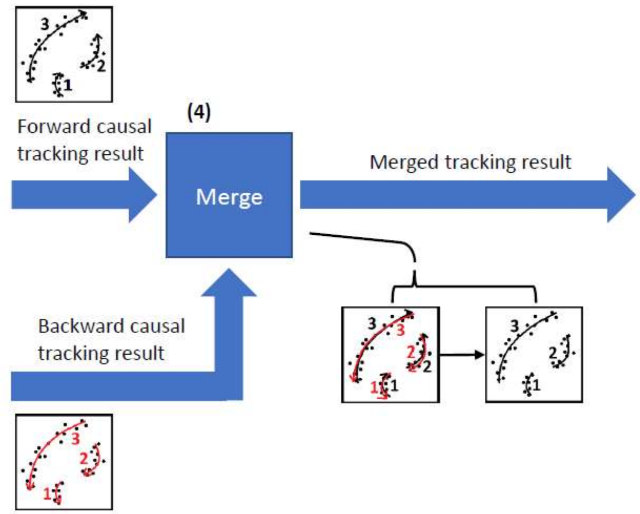
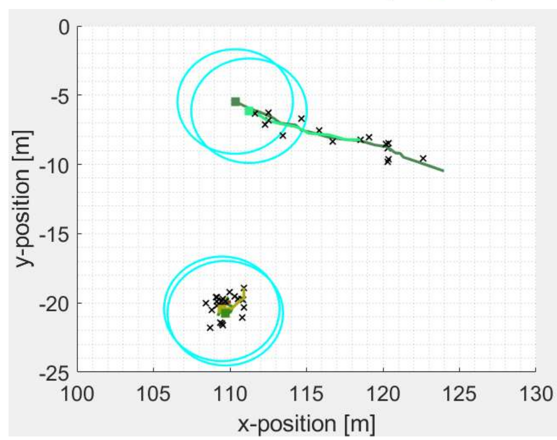
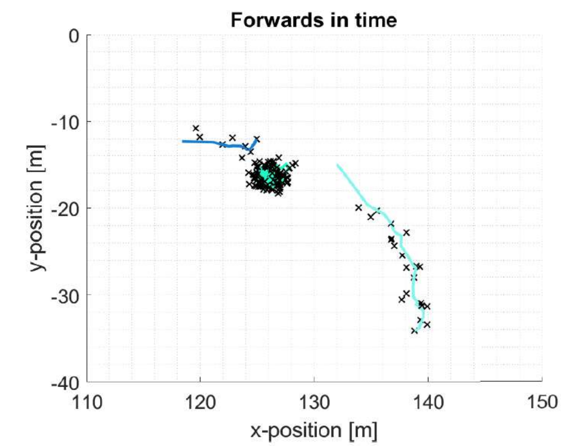


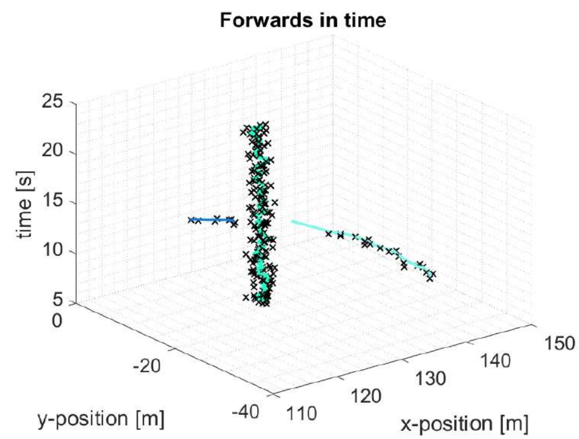
Merging forwards and backwards causal tracking result

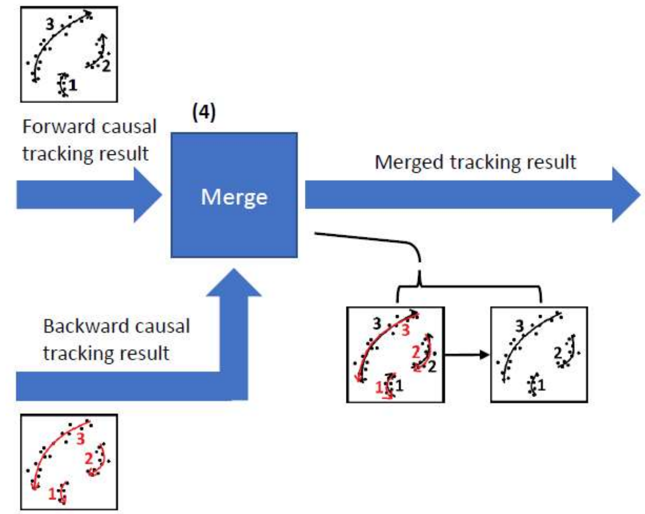
- use of the similarity gate
  - Possible tracking errors are filtered out, only similar forwards and backwards result are kept
  - Forwards and backwards objects should be within each others gate. If not, the objects are filtered out.
  - Resulting merged object is the average of the two

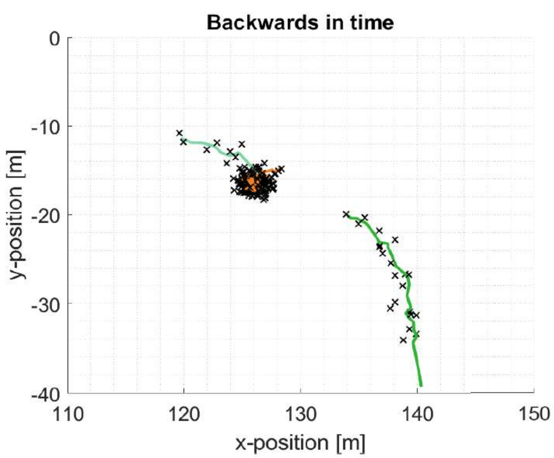


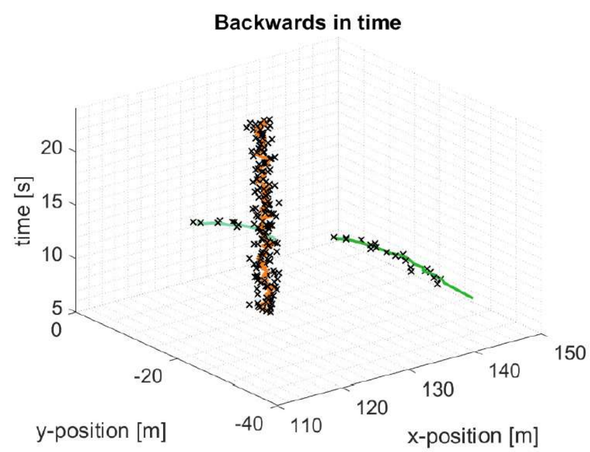
Stable tracking: merge



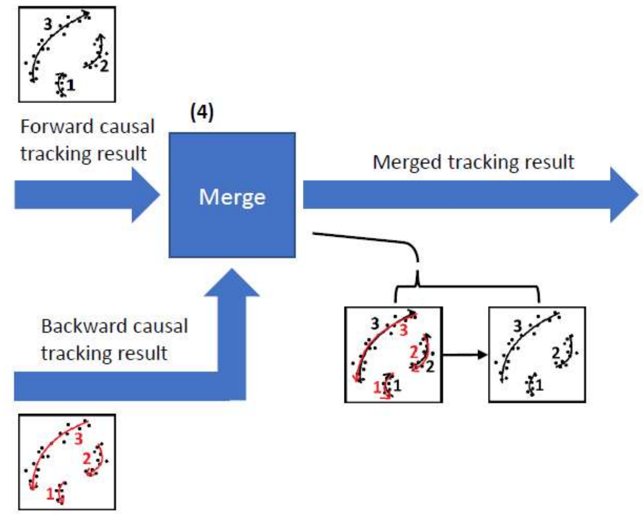


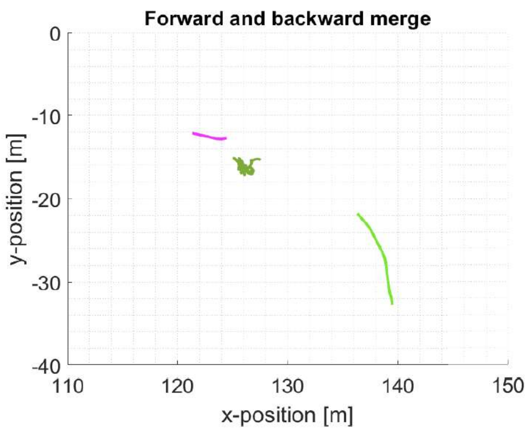


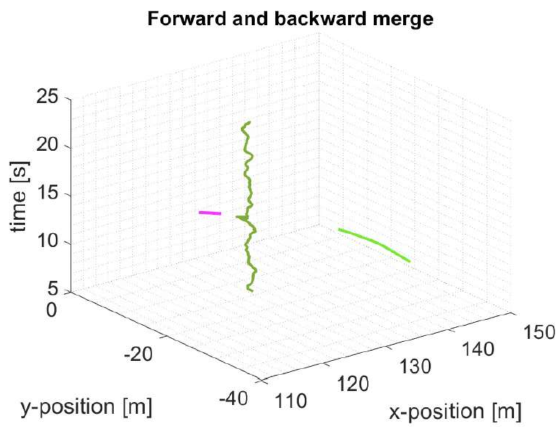




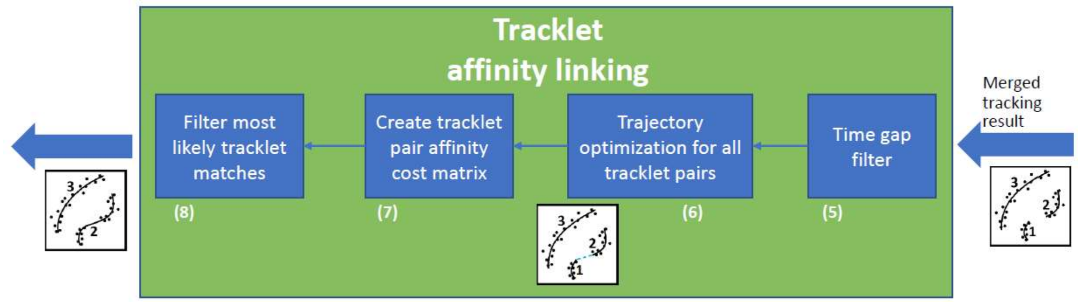
Stable tracking: merge

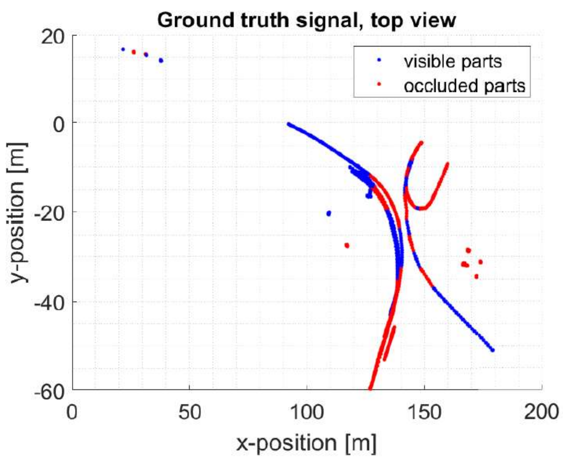


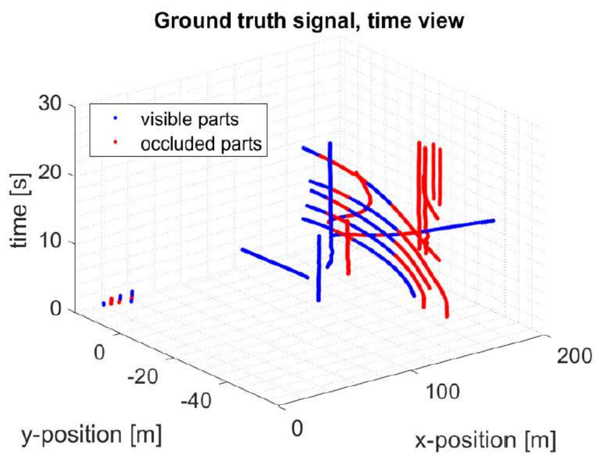


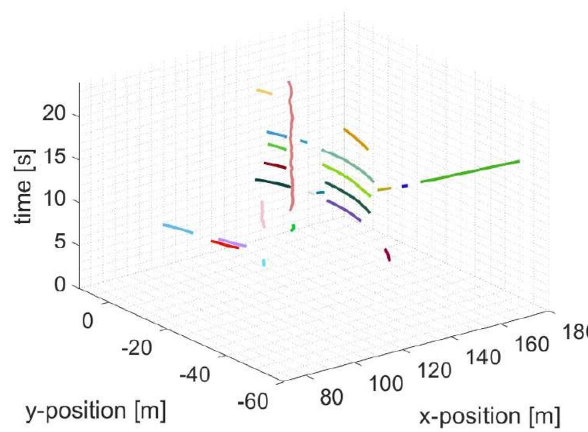


Stable tracking: tracklet affinity

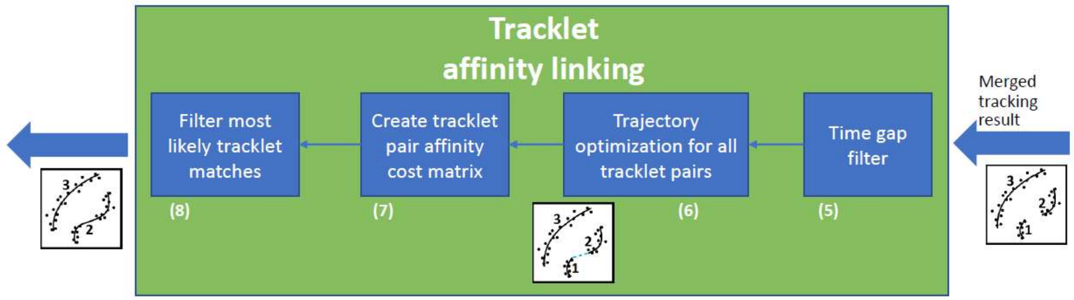








Stable tracking: tracklet affinity

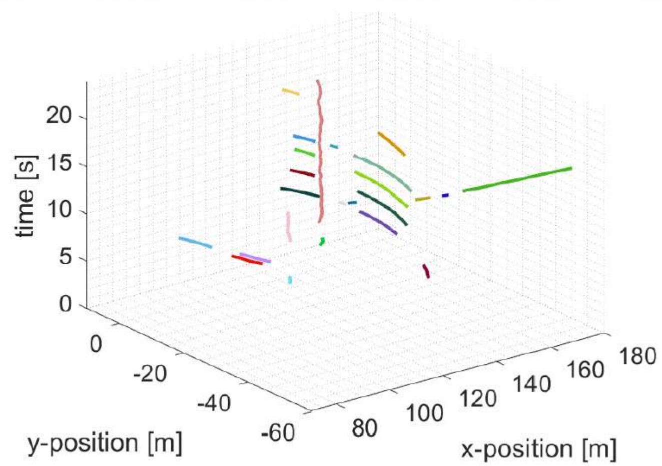


<u>Time gap filter</u>

Time gap $t_{g,2/1}$ represents the time gap between the **start** of tracklet 2 w.r.t. to the **end** of tracklet 1

$$\begin{bmatrix} 0 & t_{g,2/1} & t_{g,3/1} & \cdots & t_{g,j/1} \\ t_{g,1/2} & 0 & t_{g,3/2} & \cdots & t_{g,j/2} \\ t_{g,1/3} & t_{g,2/3} & 0 & \cdots & t_{g,j/3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ t_{g,1/j} & t_{g,2/j} & t_{g,3/j} & \cdots & 0 \end{bmatrix}$$

$$t_g \leq 0 \ \rightarrow infeasible\ to\ link$$



Stable tracking: Occlusion filling methods

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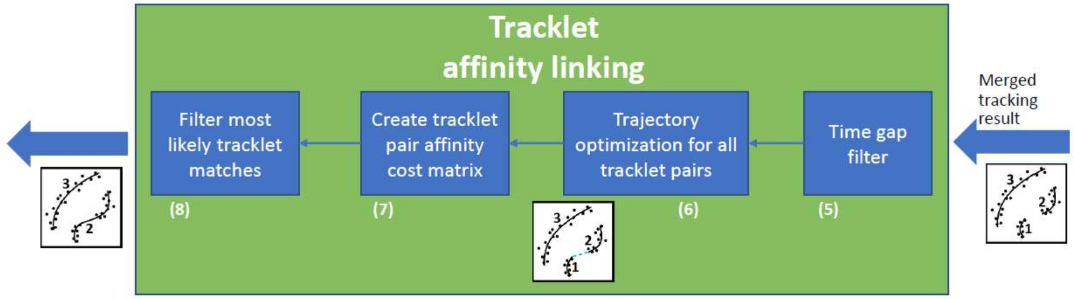
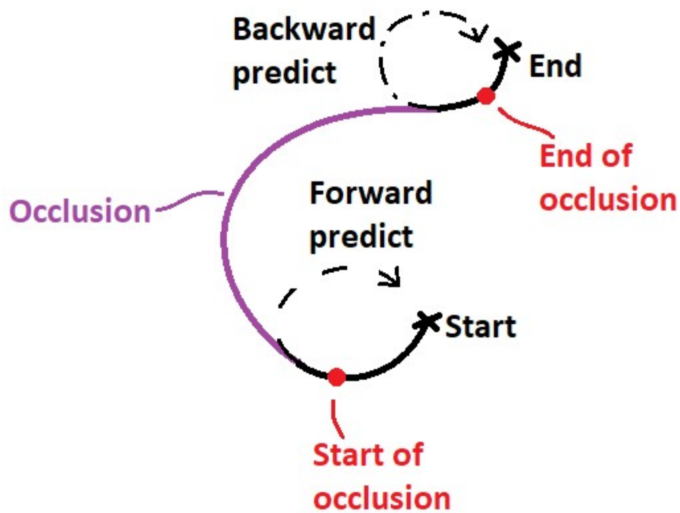
Kalman forward/backward merge

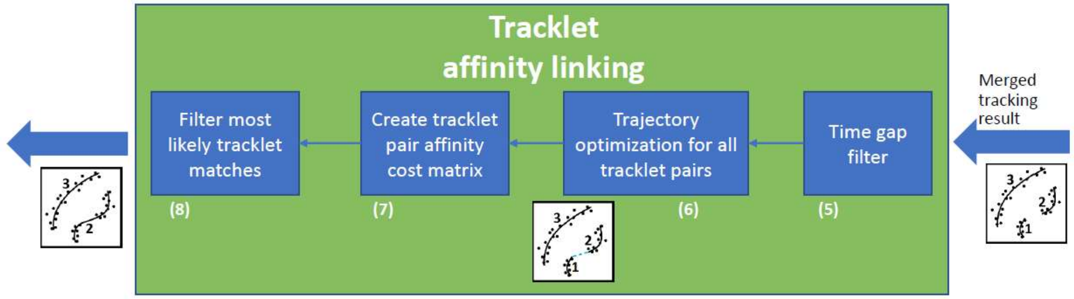


Using a merged variant of forward and backward Kalman predicted trajectories to fill an occlusion gives an important issue:

- In some situations, both the forwards- and backwards predictions are faulty. Using a linear merge will therefore not give correct results



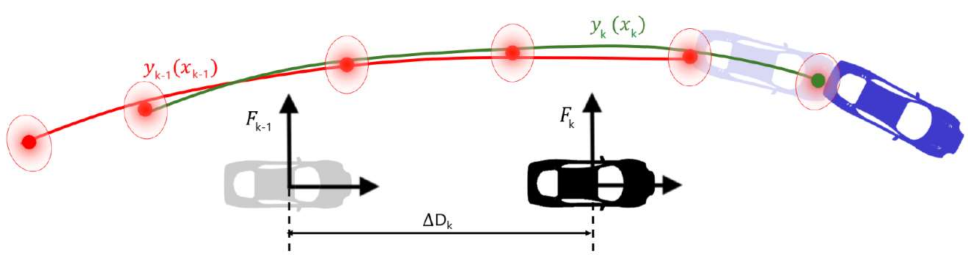
Stable tracking: Occlusion filling methods



Optimization approach

Using optimization and drive a virtual vehicle a long the way point

$$J = (x_0 - r_0)^\intercal Q (x_0 - r_0) + (\bar{x} - \bar{r})^\intercal \Omega (\bar{x} - \bar{r}) + \bar{u}^\intercal \Psi \bar{u}$$



Stable tracking: Occlusion filling methods

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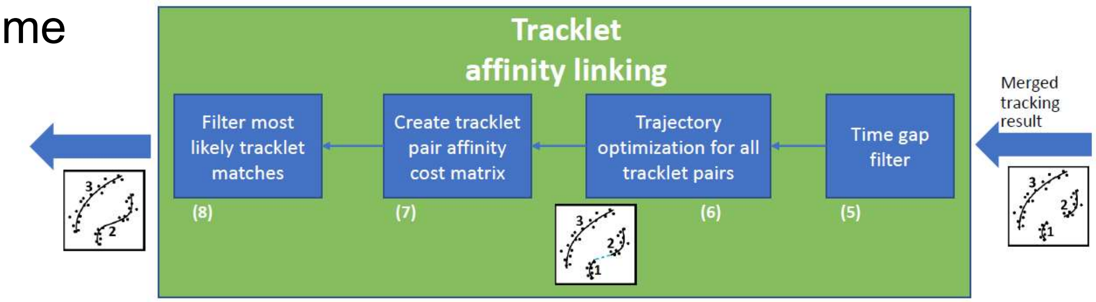
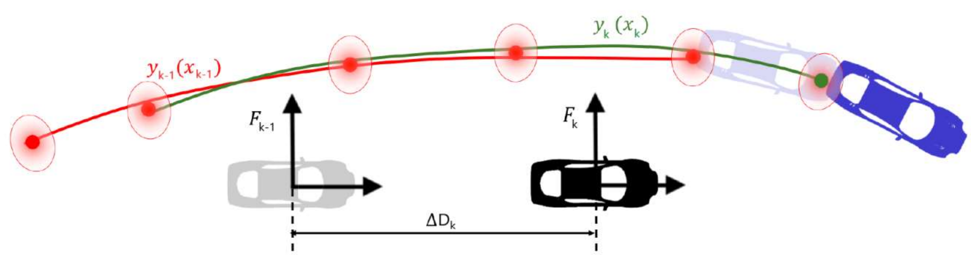
The entire state response over a finite time horizon can be computed at once:

$$\bar{x} = \bar{A}_d x_0 + \bar{B}_d \bar{u}$$



…using augmented matrices as such:

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} A_d \\ A_d^2 \\ \vdots \\ A_d^n \end{bmatrix} x_0 + \begin{bmatrix} B_d & 0 & \cdots & 0 \\ A_d B_d & B_d & \cdots & 0 \\ A_d^2 B_d & A_d B_d & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_d^n B_d & A_d^{n-1} B_d & \cdots & B_d \end{bmatrix} \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{n-1} \end{bmatrix}$$



Stable tracking: tracklet affinity

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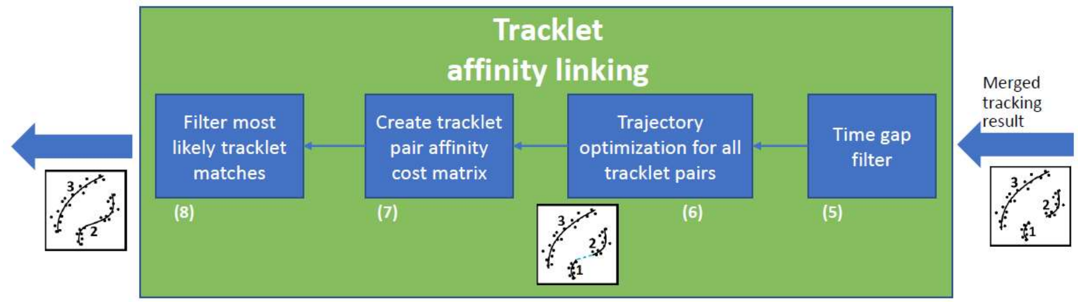

<u>(Constrained) trajectory optimization for all tracklet pairs</u>

- Minimum jerk trajectory penalizing error w.r.t. tracklet states during non-occluded parts

<u>Tracklet pair affinity cost matrix</u>

- Cost function penalizing jerk during the occlusion, and the time gap, thus favouring pairs with low jerk and short occlusions

$$\begin{bmatrix} \infty & J_{2/1} & J_{3/1} & \cdots & J_{m/1} \\ J_{1/2} & \infty & J_{3/2} & \cdots & J_{m/2} \\ J_{1/3} & J_{2/3} & \infty & \cdots & J_{m/3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ J_{1/m} & J_{2/m} & J_{3/m} & \cdots & \infty \end{bmatrix}$$

$$J_{i/j} = \max\left(\left[\|\vec{j}_{occl.\,start_{i/j}}\|_2 \ \cdots \ \|\vec{j}_{occl.\,end_{i/j}}\|_2\right]\right) t^2_{gap_{i/j}}$$

Stable tracking: tracklet affinity

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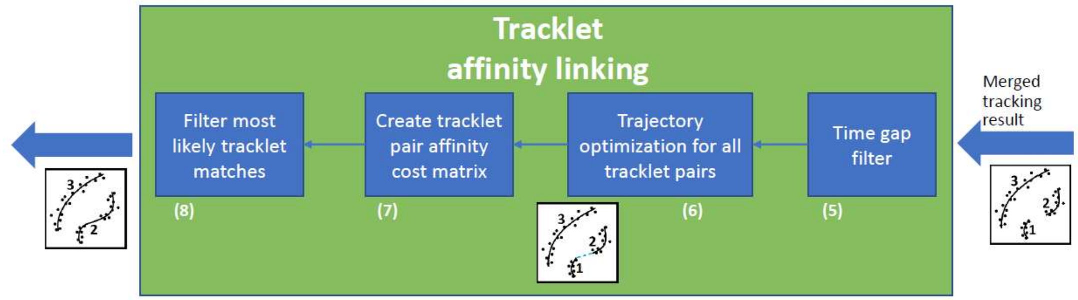


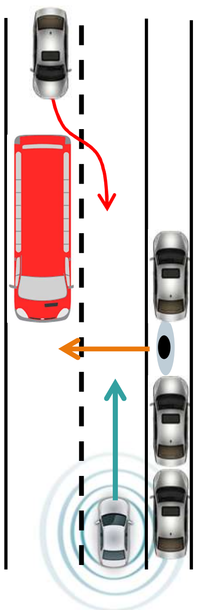
<u>(Filter most likely tracklet matches</u>

- Minimum cost of all combined tracklet pairs is found using the Hungarian algorithm (with additional no-link cost)

$$\begin{bmatrix} \infty & J_{2/1} & J_{3/1} & \cdots & J_{m/1} \\ J_{1/2} & \infty & J_{3/2} & \cdots & J_{m/2} \\ J_{1/3} & J_{2/3} & \infty & \cdots & J_{m/3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ J_{1/m} & J_{2/m} & J_{3/m} & \cdots & \infty \end{bmatrix}$$

Data collection, Post-Processing & 3D Env. generation

Unknown-Unsafe Scenarios



Phase I: Data collection, Post-Processing & 3D Env. generation → Phase II: Scene selection & Basic scenario elements extraction → Phase III: Massive scenario & test case generation → Phase IV: Generation of Unknown-Unsafe Scenarios

Unknown-Unsafe Scenarios in Different ODDs

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